Scholarly insight Spring 2018: a Data wrangler perspective

Other

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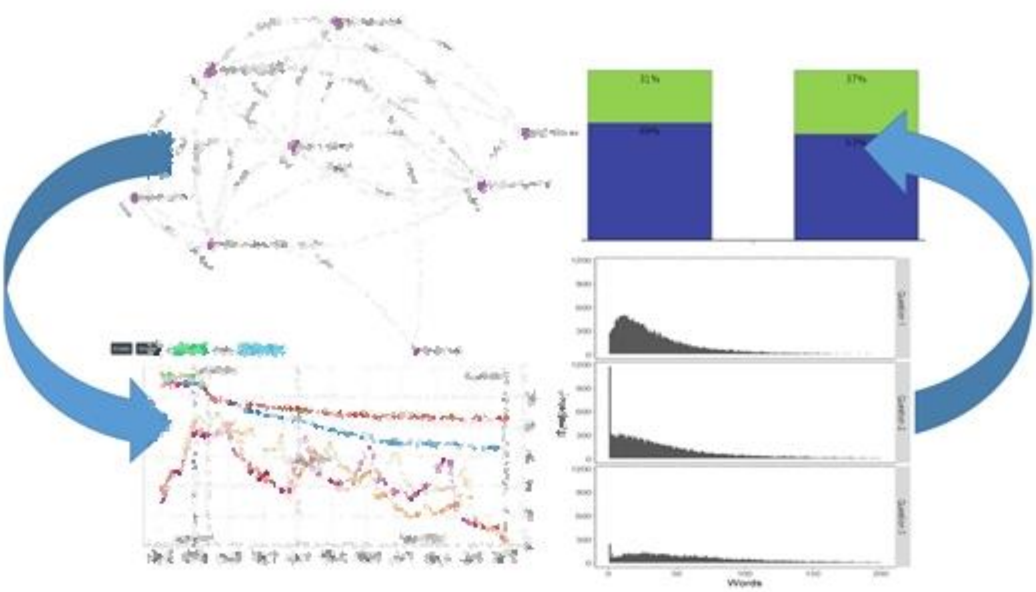

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The Open University

LTI/IET Data wranglers

				
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	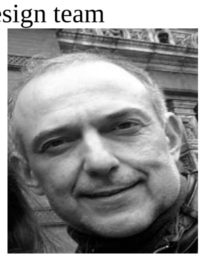			
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FOREWORD

In the movie classic *Back to the Future* a young Michael J. Fox is able to explore the past by a time machine developed by the slightly bizarre but exquisite Dr Brown. Unexpectedly by some small intervention the course of history was changed a bit along Fox's adventures. In this fourth Scholarly Insight Report we have explored two innovative approaches to learn from OU data of the past, which hopefully in the future will make a large difference in how we support our students and design and implement our teaching and learning practices. In Chapter 1, we provide an in-depth analysis of 50 thousands comments expressed by students through the Student Experience on a Module (SEAM) questionnaire. By analysing over 2.5 million words using big data approaches, our Scholarly insights indicate that not all student voices are heard. Furthermore, our big data analysis indicate useful potential insights to explore how student voices change over time, and for which particular modules emergent themes might arise.

In Chapter 2 we provide our second innovative approach of a proof-of-concept of qualification path way using graph approaches. By exploring existing data of one qualification (i.e., Psychology), we show that students make a range of pathway choices during their qualification, some of which are more successful than others. As highlighted in our previous Scholarly Insight Reports, getting data from a qualification perspective within the OU is a difficult and challenging process, and the proof-of-concept provided in Chapter 2 might provide a way forward to better understand and support the complex choices our students make.

In Chapter 3, we provide a slightly more practically-oriented and perhaps down to earth approach focussing on the lessons-learned with Analytics4Action. Over the last four years nearly a hundred modules have worked with more active use of data and insights into module presentation to support their students. In Chapter 3 several good-practices are described by the LTI/TEL learning design team, as well as three innovative case-studies which we hope will inspire you to try something new as well.

Working organically in various Faculty sub-group meetings and LTI Units and in a google doc with various key stakeholders in the Faculties, we hope that our Scholarly insights can help to inform our staff, but also spark some ideas how to further improve our module designs and qualification pathways. Of course we are keen to hear what other topics require Scholarly insight. We hope that you see some potential in the two innovative approaches, and perhaps you might want to try some new ideas in your module. While a time machine has not really been invented yet, with the increasing rich and fine-grained data about our students and our learning practices we are getting closer to understand what really drives our students.

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EXECUTIVE SUMMARY

1. Understanding SEaM student comments from a Big Data perspective: what are students saying?

OU students contribute over ten thousand comments each year to the Students Experience on a Module (SEaM) survey. Previous research has found that analysing SEaM data using a big data perspective can be useful to understand how students' experiences across hundreds of modules can be compared and contrasted (Li, Marsh, Rienties, & Whitelock, 2017; Rienties, Clow, et al., 2017). Using big data techniques, Chapter 1 looks at student comments of the OU wide administered Students Experience on a Module (SEaM) survey. Building on previous work (Ullmann, 2017a), it applies a big data perspective to the analysis of the tens of thousands of comments received by the university as feedback. It uses automated empirical text analysis methods to gauge the hot topics that students talk about in an academic year, and it evaluates the sentiment that students express towards these topics.

Chapter 1 has found that some students are more likely to leave comments than others. Women and respondents from higher socio-economic backgrounds are statistically more likely to leave comments, while respondents from lower socio-economic backgrounds write shorter comments. Comment length is not affected by gender or disability. Given that around 20-30% of students complete the SEaM survey, and of these only 83% provide at least one comment, as found previously one needs to be mindful that students' comments do not represent all unique student voices.

> Recommendation 1: Interpretation of SEaM comments must take in to account whether some student groups are over- or under-represented in the comments made.

Another important finding from Chapter 1 is that in each year the distribution of topics that respondents mention changes. Some topics and key words are unusually common in some years (e.g., Group Tuition Policy) when compared to others. However, there are other topics or key words that are mentioned consistently every year. Automated methods of analysis can identify which topics are more or less common in a particular year and compare against programme, Faculty or university norms.

> Recommendation 2: Automated methods of text analysis can help module and programme chairs determine the topics that should be prioritised. The comparative element of this analysis means the approach would be of value to large and small population modules.

Finally, we applied sentiment analysis to understand "what" students were commenting, and whether their feelings were positive or negative towards particular modules and learning designs. In other words, modules can be "compared" against others to determine how positive or negative student comments are on a particular issue. Preliminary findings indicate that these sentiment analysis can be useful to identify common trends in large amounts of qualitative data.

Recommendation 3: Changes in students' sentiment about topics can provide leads into the manual analysis of comments. Students' sentiment can be helpful in guiding the manual analysis of student comments towards areas of concern, but also perceived module strengths.

2. Student routes through qualifications

As highlighted by two previous Scholarly Insight reports (Rienties, Clow, et al., 2017; Rienties, Rogaten, et al., 2017), students can take many study routes through qualifications, and some may be better than others at preparing students for future study. Faculties are keen to understand which are the most popular and effective routes through programmes of study, and for different demographic sub-cohorts. Currently, Data Wranglers source this information by custom enquiries to Quality Enhancement and Learning Analytics (QELA) which is resource-intensive. In Chapter 2 a novel approach is explored with the intention of enabling enquiries to be generated and manipulated more readily by Data Wranglers (and potentially other Faculties members interested in data manipulation). We report on work carried out so far and provide examples of the types of enquiries that may be answered. To date, this work has used sample data to develop a **proof of concept**, and we describe how it can be used to address common questions asked about curriculum and its effectiveness.

Preliminary findings indicated that Faculty colleagues have welcomed an approach that can provide timely answers to questions they have around popularity and effectiveness of a specified study route and of the individual modules within programmes of study. They also find the graphical representation of data highly accessible and that it facilitates discussion. We have also found that, with little overhead, a graph based database can provide Data Wranglers, and others, with ready and efficient access to levels of study route detail that are difficult to obtain with the OU's standard database structures. Benefits include:

1. Relatively simple queries that can be built and adapted to explore students' study over straightforward or complex study routes.
2. The graphical output becomes a useful boundary object and informs discussion with colleagues.
3. Queries produce data that can be output to preferred programmes for further analysis.

Recommendation 4: Further research and up-scaling is needed to explore whether the qualification route visualisation approach is useful to OU staff.

3. Analytics4Action Review of evidence: themes emerging from the process and case studies relating to adoption of new approaches

Chapter 3 looks at initial themes coming out of the first year of the Analytics4Action (A4A) process being run by TEL Learning design team in LTI. In 2014 the PVC LT initiated a learning analytics innovation called Student Experience Programme, whereby one of the pillars within this programme was called Analytics4Action, which aimed to stimulate OU colleagues in module production and module presentation to work together and to explore more active use of data, and where possible provide actionable insight and intervention in or after a respective presentation. Building on the initial positive findings and encouraging support from OU colleagues on the A4A approach (Herodotou et al., 2017; Rienties, Boroowa, Cross, Farrington-

Flint, et al., 2016; Rienties, Boroowa, Cross, Kubiak, et al., 2016), the A4A approach was moved into Business as Usual in 2016/17. This applies an analysis across findings and actions for all of the modules in scope to identify the core themes being raised as issues by module teams. Four substantial trends were identified when working with 29 module teams: workload issues; knowledge or skills gaps; retention issues, and community and collaboration difficulties.

Using concurrency data from the dashboard, Chapter 3 examines how many of the modules being studied concurrently by students had TMA deadlines which fell within the same week. Several clashes and overlaps were identified. In terms of knowledge, five modules expressed concerns about 'jumps' in difficulty of material, while eleven modules either reported concern about students' preparedness for the material, or had a higher number of students with lower prior knowledge when compared with the university average. In terms of retention, four module teams were concerned that funding was affecting retention, and several were concerned about the impact of group tuition policy (GTP) and unavailability of the Virtual Learning Environment (VLE). Finally, eight modules had concerns about student isolation and the collaborative elements of the module, but these concerns were very mixed. In follow-up three case studies were explored how the learning analytics available for an individual presentation of a module have been utilised in the 2016/17 A4A process. Overall, Chapter 3 illustrates the power to work collaboratively and intensively together with OU colleagues to address retention, student experience and design issues. Making a change in the OU practice and culture starts from the grass roots, and Analytics4Action is one of the many examples that highlight that by working together amazing new and effective innovations can be developed and sustained.

> Recommendation 5: Further research and up-scaling is needed to explore for which modules and why the Analytics4Action approaches were successful, and how lessons-learned can be shared with colleagues.

> Recommendation 6: The OU needs to continue their investment into appropriate within- and across module data visualisations of students' journeys, which allows OU colleagues to make inventions when the learning design activities are not reaching their expected goals.

Note that in this public version we have anonymised all names and codes of OU modules and qualifications. For OU staff who have access to Intranet, you can download the full results at http://intranet6.open.ac.uk/learning-teaching-innovation/main/data-wrangling

1 UNDERSTANDING SEAM STUDENT COMMENTS FROM A BIG DATA PERSPECTIVE: WHAT ARE STUDENTS SAYING?

Highlights

1. Analysis of 51,000 SEaM comments consisting of > 2.5 million words from a sample of 23 prominent (large) undergraduate modules across 2013-2017 indicate that not all student voices are heard
2. Big Data analyses show substantial differences over time in how students respond to modules and the specific themes that emerge
3. Big data analyses can help to identify common themes of students' voices, as well as unique patterns that can help module teams to identify concerns and good practice
4. Sentiment analysis of students' comments can distinguish positive vs. negative sentiment of modules and learning design activities.

1.1 Introduction

OU students contribute over ten thousand comments each year to the Students Experience on a Module (SEaM) survey. Previous research has found that analysing SEaM data using a big data perspective can be useful to understand how students' experiences across hundreds of modules can be compared and contrasted. For example, Li, Marsh, and Rienties (2016) found that highly rated modules had better (perceived) teaching materials, clear assessment criteria, as well as better support from teachers in comparison to below-average rated modules. In follow-up research comparing two years of SEAM data and contrasting "new" versus continuing students, Li et al. (2017) found that these key drivers of student satisfaction change over time, and in particular the link to the qualification was perceived to be important for current students. At the same time, recent research has highlighted that there is no link between SEAM scores and student progression and retention (Nguyen, Rienties, Toetenel, Ferguson, & Whitelock, 2017; Rienties & Toetenel, 2016), thereby putting into question the relative merits of SEAM scores.

One large unexplored area of Scholarly Insight is what students are contributing in the open comment boxes (Ullmann, 2015, 2017a, 2017b; Coughlan, Ullmann, & Lister, 2017). The SEaM questionnaire contains four open-ended questions that asks students about their study experience. Answers to three of these questions are used here – the fourth concerns tutors and has been omitted from this analysis. The relevant three SEaM questions are:

- *Question 1:* What aspects of teaching materials, learning activities or assessment did you find particularly helpful to your learning?
- *Question 2:* What aspects of teaching materials, learning activities or assessment did you find not particularly helpful to your learning? We would welcome any further suggestions or comments to consider for future editions of the module.
- *Question 3:* Do you have any other comments to add about your study experience on this module?

The first two questions ask about what was helpful (positive aspects), or not so helpful (negative aspects). The third question is catch-all question to capture all other concerns. These questions give students the opportunity to provide feedback, opinion and comment in their own words about their module and, more broadly, their experience of studying at the Open University, in line with recent research recommendations (Kember & Ginns, 2012; Moskal, Stein, & Golding, 2015). Free-text response questions can be much more effective than closed-answer questions in capturing the nuance and richness of the student voice (Callender, Ramsden, & Griggs, 2014; HEFCE, 2016; Whitelock & Watt, 2009). Inspection of the SEaM responses show that students do not always directly answer the question asked and so may write about issues such as group tuition or talk about activities that were not helpful when answering question 1.

At present most module teams analyse student comments 'long-hand' - by reading each comment in turn. Analysing these using conventional qualitative methods is time consuming and potentially subject to bias in identifying themes, especially if being done quickly. This analysis adopts an empirical big data perspective to produce insights about:

- What topics students talk about;
- How topics change in prominence over time;
- How positive or negative students feel about these topics.

1.2 Method and approaches used

This report presents initial analysis of over 51,000 comments from a sample of 23 prominent (large) undergraduate modules. These comprise a substantial dataset on which to trial the techniques outlined below. The approach adopted in this report is a form of computerised text analytics (Jeonghee, Nasukawa, Bunescu, & Niblack, 2003; Ullmann, 2015, 2017b; Ullmann, Wild, & Scott, 2012; Wen, Yang, & Rosé, 2014). This is a method that can be applied to large datasets and thus allows us to perform analysis on student comments from many modules. However, a limitation of this approach is that it lacks the understanding of written text as well as the context in which students left their comments. The position of this paper therefore is that the automated analysis cannot replace the manual analysis, but it can provide means to assist the sense making of student comments. With regards to the manual analysis of SEaM comments, module teams can rely on the existing guidance in reviewing their feedback offered by the Quality Enhancement and Learning Analytics team.

The analysis is based on answers to the 2013-2017 version of the SEaM survey. In early 2018 a new version was introduced and this made changes to two of the three questions under investigation. The only open-text question that is shared between questionnaires is: 'Do you have any other comments to add about your study experience on this module?'. It has yet to be determined whether analysis of modules with the old and new SEaM surveys will be comparable.

University policy permits the use of SEaM data for learning analytics and before the survey students are explicitly told about the data protection policy of the university and that their data can be used for research and quality enhancement purposes. The analysis of open-text comment data presented below conforms to these stated uses and data is anonymised before use.

1.3 Findings

1.3.1 Length of student comments

Analysis shows that over 2.5 million words were used by students in the *subsample* of 51,000 comments used in this analysis. Furthermore, whilst the number of comments decline from question 1 to question 3, the number of words increase. On average students that write a comment to question 1 write 40 words, 48 for question 2 and 67 for question 3, see Table 1.1. To put this in context, given a reading speed of 250 words per minute it would take two months to read all these comments (16 working days to read all answers to question 1 and 2, and nearly 7 days for question 3)[1]. In addition, of course it would take much longer to code, analyse and interpret the comments.

Table 1.1 Reading time estimates

Column1	Comments	Sum of words	Mean word count	SD	Estimated reading time [hours]
Comment 1	22,196	887,239	40	45	59
Comment 2	18,362	881,739	48	58	59
Comment 3	10,842	727,590	67	63	49

1.3.2 Who are the students that comment?

When analysing student comments, we tend to focus initially on categorising and ordering the seemingly diverse range of statements written by our students. In line with good-practice guidelines (Biggs & Tang, 2007; HEFCE, 2016; Kember & Ginns, 2012; Moskal et al., 2015), often the goal of module chairs is to arrive at a set of key themes or topics that can help to provide focus for the improvement of the module as well as to better understand the “strengths” and “weaknesses” of the module. These analyses are based on the students’ comments in front of them, yet it can be difficult to know if these comments are representative of the group who responded to the SEaM survey (let alone whether the respondent to the survey are a good reflection on student experience for all on the module). Do some students tend to answer the open-text comments more than others? Are there discernible variations between groups of students by gender, socio-economic status or disability for example? Should it matter that we may not have as many comments from some sub-groups of students?

Participation in SEaM is voluntary so not all those students respond to the survey (Li et al., 2016; Li et al., 2017) and, from the students that do respond, not all write comments. Answering any question in SEaM, including the open-text comment questions is not mandatory so this is to be expected. So how much variation in commenting can we see in answers to SEaM? On average, a module can expect that 24% of students that have been invited to participate will answer closed-questions in the survey as well as leave at least one comment. That is 83%[2] of students that participate in SEaM will leave at least one comment. So are the

[1] It would take on average 109 minutes (SD = 63 min) to read all comments of a single module presentations.
[2] Percentage of the comment response rate over all modules.

83% of commenting students are different from the 17% of students who filled out the questionnaire but did not write a comment?

In respect to gender, female students comment[3] significantly more often than male students ($X^2(1) = 150.76$, $p < .0001$), see Table 1.2. The odds of writing a comment are 1.5 times higher if the student is female compared to male students. This significant difference holds true also when considering students from FACULTY1, FACULTY2, and FACULTY3 but there is not gender difference in comment making for FACULTY4 and FACULTY5[4].

Table 1.2 Results of Chi-squared analysis to determine whether non-response significantly varies for gender, socio-economic status and disability per Faculty

	Gender		***Socio-economic status***		***Disability***	
Faculty	$X^2(1)$	***p***	$X^2(1)$	***p***	$X^2(1)$	***p***
All	150.76	.00**	18.36	.00**	0.99	.32
FACULTY1	19.27	.00**	8.52	.00**	0.65	.42
FACULTY2	8.57	.00**	0.02	.88	1.46	.23
FACULTY5	0.02	.89	0.00	1.00	0.03	.86
FACULTY3	37.15	.00**	7.86	.01**	0.87	.35
FACULTY4	2.42	.12	4.24	.04*	0.67	.41

*** p <.01. *p<.05.*

In general, students from a low socio-economic background comment less often than students from a higher socio-economic background ($X^2(1) = 18.36$, $p < .0001$). The odds of commenting are 1.27 times higher if the student comes from a higher socio-economic background. This significant difference can be also found in FACULTY1, FACULTY3, and FACULTY4, but not in FACULTY2 and FACULTY5 (Table 1.2). There is no significance between students that declared a disability and students that did not ($X^2(1) = 0.99$, $p < .32$). This holds true for all five Faculties.

The analysis shows that some student characteristics can influence whether a student will write a comment or not and indicates that further investigation into other characteristics is necessary. However, are there also differences in terms of how much students write? Do some tend to go into more detail or say more than others?

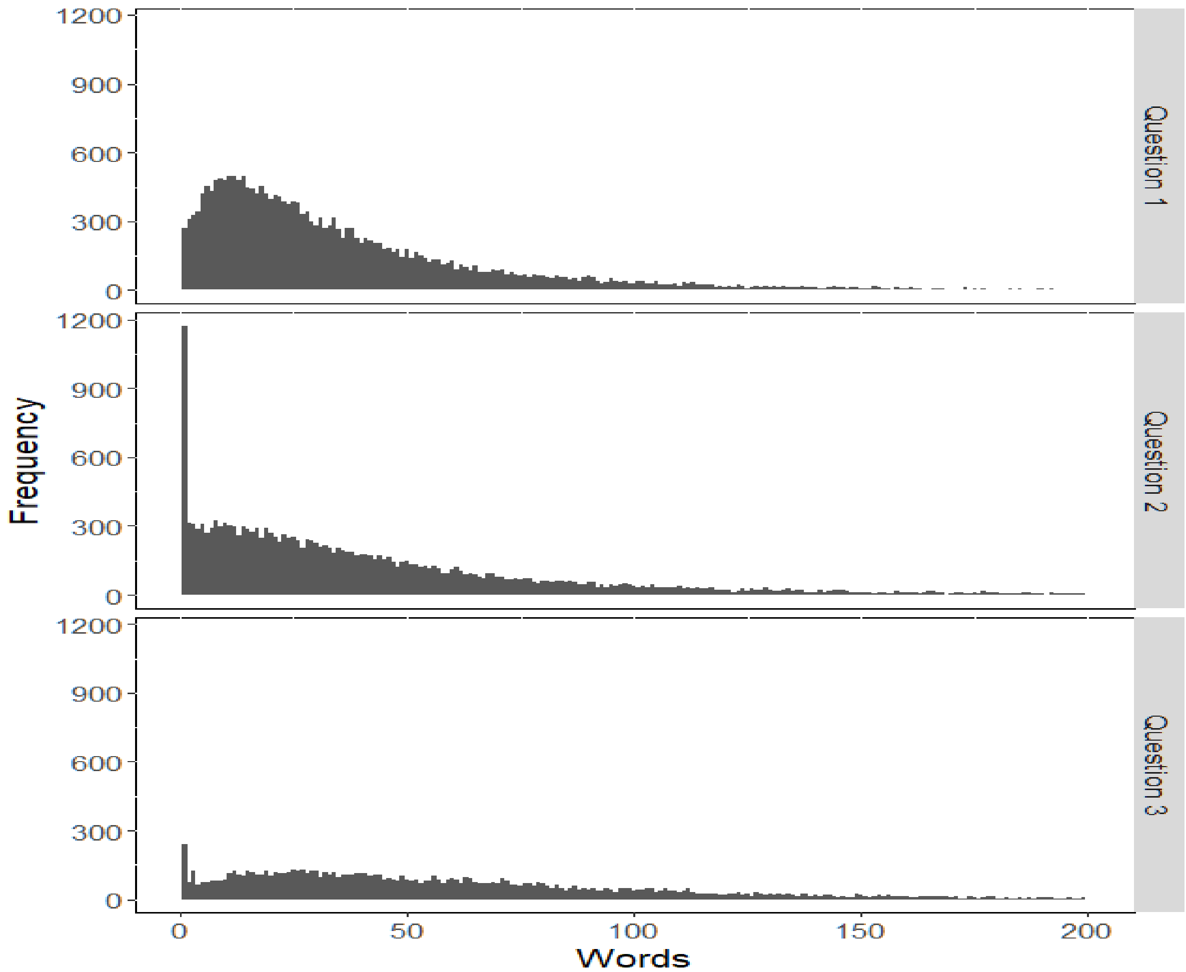
Figure 1.1 shows three histograms of word frequencies for each of the three open SEaM questions. Overall, most students write comments in the range of 1-50 words and fewer students write longer comments. Of particular note is the bar in question 2 and to a lesser extent in question 3. These are comments indicating no answer, such as n/a, na, no, etc. On average, comments of female students are 114 words long and the comments of male students 111 words (median for female students 84 words and 77 words for male students). This is not a great difference ($W = 57203854$, $p < .0001$, $r = -.03$). There is a median difference of 10 words for FACULTY1, 10 words for FACULTY2, 4 for FACULTY5, 1 for FACULTY3, and 11 for

[3] At least once.

[4] Regarding the anonymization, see the note at the end of this topic

FACULTY4 (Table 1.3) but in most cases the differences are not statistically significant. Students from low socio-economic status write on average shorter comments (Mean = 103, Mdn = 74) than students from a higher socio-economic status (Mean = 113, Mdn = 82, W = 17035319, p < .0000, r = -.03). The median differences persist within each Faculty (Table 1.3), with a word difference of 13 for FACULTY1, 8 for FACULTY2, 8 for FACULTY5, 10 for FACULTY3, and 10 for FACULTY4.

Figure 1.1 Word frequencies in 3 open questions SEaM



Students that declared a disability write on average longer comments (Mean = 115, Md = 82) than students that did not declare a disability (Mean = 112, Md = 81) but these differences are not significant (W = 25710453, p = .36, r = -.00). The median difference continues on Faculty level (Table 1.3), with a difference of 1 word for FACULTY1 and 3 for FACULTY3, while FACULTY2, FACULTY5, and FACULTY4 show longer comments of students without declared disability with a median of 7, 9, and 4 respectively. None of these differences are statistically significant.

This analysis shows that students who give written comments are different from students who elect not to give comments and only responded to the multiple-choice questions of the survey. Not only are there participation differences, but there are also differences regarding the length of their student comments. A difference of a few words may not look much, but these small sizes accumulate with rising student numbers.

Table 1.3 Summary of results of Wilcoxon rank test

	Gender		Socio-economic status		Disability	
Faculty	*R*	***p***	*r*	***p***	*r*	***p***
All	-.03	.00**	-.03	.00**	-.00	.36
FACULTY1	-.04	.00**	-.04	.00**	-.00	.73
FACULTY2	-.06	.09	-.01	.78	-.02	.67
FACULTY5	-.01	.71	-.00	.96	-.02	.63
FACULTY3	-.01	.51	-.02	.11	-.02	.09
FACULTY4	-.03	>.05	-.03	.03*	-.00	.75

*** p <.01. *p<.05. Due to the heavy skew of the distribution we used the non-parametric Wilcoxon rank-sum test.*

Overall, the analysis shows that for some Faculties and for some socio-demographic variables there are differences between the group of students that participated in SEaM and the group of students that also provide written feedback (and also in the length of their writing). Therefore, the voice of those students who respond to SEaM may not represent the voice of all students. In line with Recommendation 1, any decisions that are based on the analysis of the SEaM student comments should consider groups of students that may not be represented in the student comments due to the comment non-response bias.

1.3.2 What are students talking about?

There are some topics that students appear to talk about every year. Only to mention a few: the module, the course, the tutor, the tutorials, materials, books, activities, etc. These are words that are mentioned year after year. Each year, however, there are topics that students talk about unusually often (or less often). These are topics that they may have talked about in other years, but for a specific year we notice an unusual rise in frequency of the topic in the comments. The log-likelihood statistic is used to discern topics that students talk about every year from topics that are particular for a given academic year (Ullmann, 2015, 2017a, 2017b; Coughlan et al., 2017).

Table 1.4 shows a cut-down list of (multi-noun) words ordered by their log-likelihood (LL). This statistic takes into account the frequency of each words, but also the overall frequency of words to adjust for data sets with different word sizes. The greater the LL, the more unusual frequent is the occurrence of that word in a year compared to all other years. For example, the multi-noun word “face-to-face tutorials” was the word with the highest log-likelihood. This means that is was mentioned unusually frequently in 16J compared to all other years. In 16J it was used 560 times and in all other years (reference years) only 1432 times (the reference data set is much larger, containing all years from 13J to 16J). The table also indicates if the word was used more frequently in the year of interest (the actual year) than in the reference data set. This is indicated by the plus sign. The minus sign indicates that the word has been underused in the current year.

For 2016J, an inspection of the word list shows that students talked unusually often about *face-to-face tutorial(s), tutor(s), face-to-face, tutorial(s), and online tutorials*. Also, they talked about the *system or booking system*. Dates and distances seemed to be a topic indicated by words such as *year, date(s), miles, and distance*. There was a lot of talk about the *module, module website, credit module, and module material(s)*, but also mention of *confusion, lack, stress, and problems*.

Table 1.4 Excerpt of What students are talking about

Term	Actual WC	Reference WC	LL	use
facetoface tutorials	560	1432	209.62	+
tutors	434	1493	68.39	+
tacetoface	117	254	60.67	+
system	111	253	52.64	+
tutorials	1197	5242	49.27	+
year	330	1191	42.73	+
booking system	32	32	41.88	+
online tutorials	140	403	39.18	+
course	1345	8804	35.78	-
date	185	632	29.94	+
…	…	…	…	…

+ more frequent use in 16J. - less frequent use in 16J
Log-likelihood 16J vs all

A year earlier in 2015J the list of relatively 'overused' words suggests a different focus from 16J (see Appendix A.1.3). They talk about *practise, about module resources, such as the module book, networking book, textbook, websites, wiki, and eportfolio*. Students also are talking about certain subjects, such as *linux, robotics, networking, software, business, and education*, but also about values, such as *diversity, learning, and benefits*. The final year analysed was 2014J (see Appendix A.1.4). In this year words are about *activity*, and *group activity*. But also about materials, such as *guides, dvds, dvdrom, reading materials, printing, blocks*, and *exam*.

From this investigation we can see that each year students seem to talk about certain topics more often than usual. Additional manual analysis could begin to further investigate the reasons for these changes in emphasis. An important element of this could be an assessment whether students are generally more positive about the topic or more negative (see below). The OU-wide analysis of SEaM comment data provides an empirically derived perspective about topics that are important to students. These topics can provide an entry point to the manual analysis of the SEaM comments on module level by the module chairs. Especially for modules with large amounts of comments, module chairs should consider automated methods as a possible entry point to the manual sense-making of student comments (see also Recommendation 2).

1.3.3 Determining sentiment of SEaM over time

Sentiment analysis combined with a dictionary-based text analysis offers a method of estimating the balance of positive and negative comments made by students (Jeonghee et al., 2003; Warriner, Kuperman, & Brysbaert, 2013; Wen et al., 2014). The sentiment analysis of the comments can provide extra information, which scores derived from the closed questions alone cannot provide, as they do not tell us why students choose to rate their study experience in such way. Furthermore, the open-ended questions may capture topics, which the closed-questions do not cover, adding another benefit of the combination of topic with sentiment analysis.

Table 1.5 Crosstable of sentiment by presentation years

Presentation	Negative	Positive	Total
2013J (actual)	2299	1135	3434
2013J (expected)	2312.9	1121.1	
2014J (actual)	2166	1075	3241
2014J (expected)	2183	1058	
2015J (actual)	1751	852	2603
2015J (expected)	1752.2	849.8	
2015J (actual)	1424	641	2065
2015J (expected)	1390.9	674.1	

In Appendix A1.4 the exact specifications and details of the sentiment analysis approach adopted are provided. Using this process, we determine how many students expressed a positive sentiment and how many negative comment for each year from 2013[5]. In Table 1.5 the following Crosstable tabulates these counts, whereby the first and second row provide the actual frequency of students and an expected frequency (as calculated as part of the Chi-square analysis). For example, for 2013J the test estimates 2313 students should show a negative sentiment about tutorials, whereby indeed 2299 actually had a negative sentiment. In 2013, therefore, slightly more students had a positive sentiment than expected.

In 2013J, 2014J and 2015J more students expressed a positive sentiment about tutorials than was expected by the statistical model. However, in 2016J there is a reversal in sentiment and more students than expected showed predominantly negative sentiment about the topic of tutorials[6]. This technique is identifying an issue that is known to exist in relation to the implementation of the Group Tuition policy and systems[7].

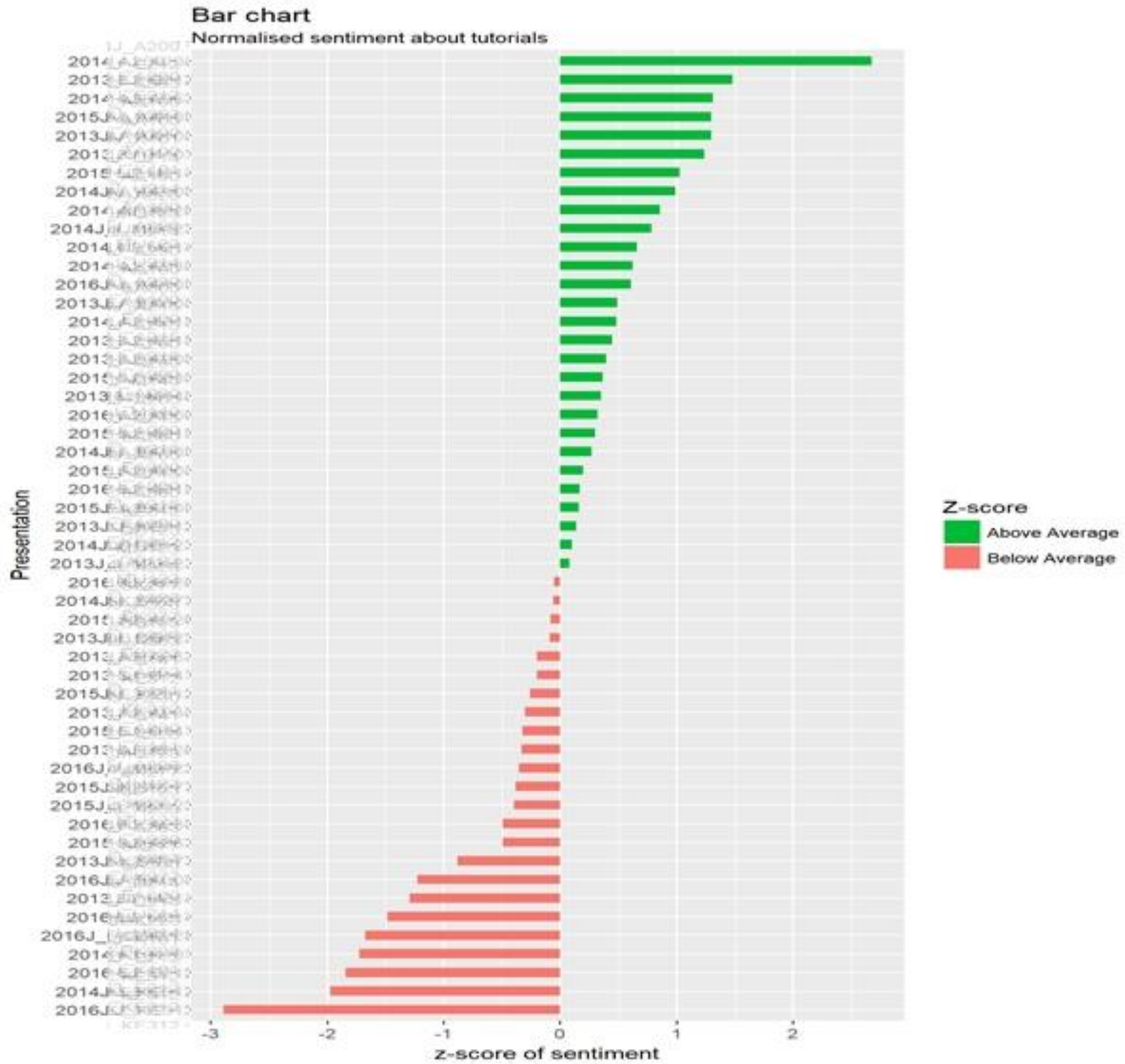
1.3.4 Comparing sentiment scores between modules

Figure 1.2 shows a selection of high-population modules and the (module level) aggregated mean sentiment score for different presentations of that module. The means of each module in this visualisation have been normalised in form of z-scores[8]. Z-scores show how far, relative to

[5] Sentiment has been aggregated by averaging all the sentiment expressed by a student about a topic per presentation and afterwards it has been dichotomised. The mean ranged from 1 to 3. A mean score that equals or is smaller than 1.5 has been assigned the sentiment negative. otherwise it has been assigned the sentiment positive.
[6] Analysis using the X2-tests (comparing pair-wise for all years) found there to be significant differences between the 2016J presentation and each of the three preceding years (e.g. 13J vs 16J, 14J vs 16J, 15J vs 16J). There was no significant difference between other presentation years (e.g. 13J vs 14J, 14J vs 15J, 13J vs 15J).
[7] For more information, see the final report of the Working Group on the Academic Evaluation of the Group Tuition Policy (GTP) presented to the Senate (S-2018-01-10) and Ullmann (2017a).
[8] A common boundary for determining significant outliers are < -1.96 or > +1.96 (this mean there is a more than 95% chance that this module is distinctly different from those on the average - or in statistical terms, it is associated with a small p-value of $p < 0.05$). In the group analysed, two modules lie below the -1.96 threshold indicating an unusually high number of negative comments compared to the other modules. One module exceeds the + 1.96 threshold indicating an unusually positive sentiment score.

the other modules included in the analysis, the module presentation is from the mean of all the modules included in the analysis. Most of the mean scores for individual modules will centre around the global mean (the mean of all the modules), but there will be outliers with higher z-scores that stand out.

Figure 1.2 Normalised sentiment by presentations



The method of determining sentiment z-scores for modules could be invaluable for comparing modules within a programme or school and identifying underlying temporal changes in sentiment. This could assist in taking decisions about which modules comments need further analysis or additional focus. For example, A01 and A02 received relatively more positive comments than other modules, while A03 and A04 received relatively more negative comments. By using an integrated approach of learning design, learning analytics data and Analytics4Action (see Chapter 3), several lessons can be learned when analysing modules with high positive sentiment, as well as understanding why students indicate more negative sentiment towards other modules.

Interpretation of open comments should be made with consideration of a relative sentiment score. This measure of sentiment should locate the module historically - by comparing with previous presentations - and globally - by comparing it with comments left by students on other modules. Strong, as well as weak, presentations could thus be identified (See Recommendation 3).

1.4. Summary

All the analyses above considered tens of thousands of students' comments from prominent J modules over the last four years. Given that it is an intractable problem to manually analyse large amounts of student data, the analyses showed the potential of automated methods to analyse student comments beyond the module level. The analysis showed the application of two text analysis methods, one to determine topics and the other one to determine sentiment, which in tandem provide useful insights.

The log-likelihood method identifies topics that students talked about much more than would be expected. It can guide efforts to further analyse trends in comments, which can look to identify the reasons behind the prominence of these topics, why students talk so much about them, and whether the comments suggest specific areas for attention or actions that can be taken in response. Adding sentiment analysis can identify topics where the student respondents change their views over time. Knowing this can support us to target these topics and to evaluate the reasons behind such changes.

Our analysis of the likelihood of commenting and the length of comments should raise awareness that responses should be considered with regards to the group of students that write these comments. We have shown that student characteristics such as gender and socio-economic status can influence commenting behaviour. This is important to bear in mind when making generalisations about the whole student cohort, whether based on manual or automated analysis of SEaM comments.

We have demonstrated two useful techniques that could be utilised by module and qualification teams when dealing with large unstructured comment or feedback datasets. Further development, working with Faculties, could improve the analytic capabilities further, as well as exploring other techniques, like corpus linguistics. Furthermore, it would be useful to explore differences in common topics across and between different demographic groups and "typical" OU student profiles. This could provide helpful and quick supporting insight to the human readers undertaking finer manual analysis of the data. This work seeks to combine the best of both methods for future projects.

1.5 Contacts

Main authors and contacts for this study: Thomas Ullmann, Bart Rienties, Simon Cross, and Stephanie Lay.

Note that in this public version we have anonymised all names and codes of OU modules and qualifications. For OU staff who have access to Intranet, you can download the full results at http://intranet6.open.ac.uk/learning-teaching-innovation/main/data-wrangling

2. STUDENT ROUTES THROUGH QUALIFICATIONS

Highlights

1. A proof of concept to visualise qualification pathways and students' choices was tested
2. Using a Psychology qualification as exemplar, the findings indicate strong variation in students' pathway choices
3. The ArangoDB visualisation tool seems useful for OU staff to explore the complex choices students make in their qualification pathways

2.1 Introduction

Previous Scholarly Insight work has shown that the paths that students take through their qualification impacts their achievement (Rienties, Clow, et al., 2017; Rienties, Rogaten, et al., 2017). The OU's modular approach to qualifications means that for the majority of qualifications there are a large number of possible permutations of modules that can be taken to achieve a final qualification. For example, the large population QUAL1 currently offers 64 potential permutations: a qualification that the Curriculum Business Systems Team has identified as 'linear', rather than 'complex'. Understanding student choices and performance over extended module routes can enable Faculties to:

- Identify which routes are most popular
- Gain a better understanding of which module selections may prepare students for later key modules
- Identify particular sub-cohort demographics or students (e.g. at risk groups) who are performing below/average/above the general cohort along a sequence of modules

The OU has consistently provided excellent data and analyses on the performance of modules after they have presented. In recent years, strong inroads have been made into providing real-time performance during presentation (see Chapter 3), and this can be particularly useful in identifying and supporting students with difficulties in their current studies. There has, however, been an ongoing challenge in providing approaches and tools for exploring the performance of curriculum and students as they progress through the educational journey over a number of modules. These issues were raised in the two Scholarly insight reports of 2017 (Rienties, Clow, et al., 2017; Rienties, Rogaten, et al., 2017) and this Chapter continues their consideration.

The goal of Chapter 2 is to provide a potential proof of concept to enable rapid manipulation of large samples of data, that will allow multiple and complex queries around study routes to qualification to be answered and edited by Data Wranglers, and to provide answers to those in Faculties who have an interest in developing and enhancing curriculum and the student experience. To illustrate this work, we take one example of a large population first level QUAL1 module that a Faculty team wish to understand better and show, with a sample dataset, how this approach allows us to explore a range of questions that have previously been difficult to answer. Example questions we will use to illustrate the model:

1. What choices do students make after taking a first module (A05) in their subsequent study?; *(answers: how can we tell what students do over extended routes)*

2. What are the most common sequences of routes through the QUAL1 programme to A06, covering Levels 1 and 2? *(answers: frequencies of routes)*
3. Does one Key Introductory module (A05 or A07) better prepare students for the second level compulsory module A06 on the QUAL1 qualification? i.e. are students who take and pass A07 more likely to pass A06 than those who take and pass A05? *(answers: comparative success rates)*
4. Do students of a particular at-risk demographic perform as well as the general population of a cohort following a route through a sequence of modules, e.g. from A05 to A06? *(answers: sub-cohort performance compared to general cohort)*

2.2 Methods and approaches

Prompted by an increasing number of questions from Faculties, this scholarly insight investigates an alternative approach that holds promise in providing improved access to this longitudinal data (Edwards, 2017). We have been exploring one approach, making the use of recent developments in 'graph databases'. These are designed to enable data linked through complex relationships to be managed and queried. The result is that through simple queries, the data relating to students who have studied a particular series of module presentations, with specified outcomes, can be readily selected from the dataset. We consider several examples below.

After reviewing a number of potential solutions, we have trialled a leading open source system, ArangoDB (https://www.arangodb.com/). This is particularly suited to this OU context because it is well set up to manage the scale of data we are interested to explore, (ease of use for rapid experimentation by OU data manipulators), and secondly it enables generation of interactive visualisation of this data. This kind of database uses a different structure to that of conventional relational databases. The relationship between data is built into the structure, using the concepts of nodes and edges from graphs. This makes the retrieval of linked data a much more straightforward task. On initial piloting visualisation of students' routes through qualifications were found to be engaging boundary objects that facilitated conversation with Faculty staff and stimulated more in-depth querying of student performance across different routes.

A large dataset has first to be requested from LTI-Stats and QE that identifies individual students taking the desired module and presentation combinations and their performance. This data set is then initially manipulated using a bespoke programme (see Appendix A.2.3) to output the data in a format that can be imported and interrogated in the system we are using, Arangodb.

It should be noted that within the graph database, the selection of data through queries is by default based on students' actual study choices and through tracking the records at an individual PI level, identifying routes taken through modules for a specified group of students. Student records indicate qualification aim, where given and this is an optional field within the selection filter. Therefore, the model also has the ability to include data relating to students who do not declare a qualification aim.

A sample dataset, once in Arango, can be interrogated via a short script query, and the output selection produced is a table of all entries that fulfil the criteria. There is an example of a simple query in the box below. This can be exported via conversion into any standard programme like Excel, R or SPSS, if further manipulation is then desired. For example, a list could be generated of all students who started with the QUAL1 first module A05, passed, then took and passed the second A09 module and then passed the third module A10. This could be exported and queried by Faculty interested to know the demographic composite of this set of students. The query could be rapidly changed to identify the same path but for students who took and passed the third module A12 instead.

An **example** of a query. This one selects all the students who attempted the 2014J presentation of A07 and then adds to the selection all the subsequent study for each of these students. The result can be displayed graphically or as raw data. By changing the initial selection we can easily select different groups of students: for example all those who studied A07 as their first module, or those starting in 2014J either of the recommended starting modules for QUAL1: A05 and A07.

```
FOR u IN Study
 FILTER u.`Module-pres` == "A07-14J"
 LET r=CONCAT("Study/",u.pi,"-A07-2014J")
 FOR v,e,p IN 1..10 OUTBOUND r Path
 RETURN p
```

This can be used to generate a plot showing the subsequent study of the cohort: the graphical output is a built in feature, that in early trials we have found produces a visual representation that has acted as a trigger to conversation when shared with Faculty.

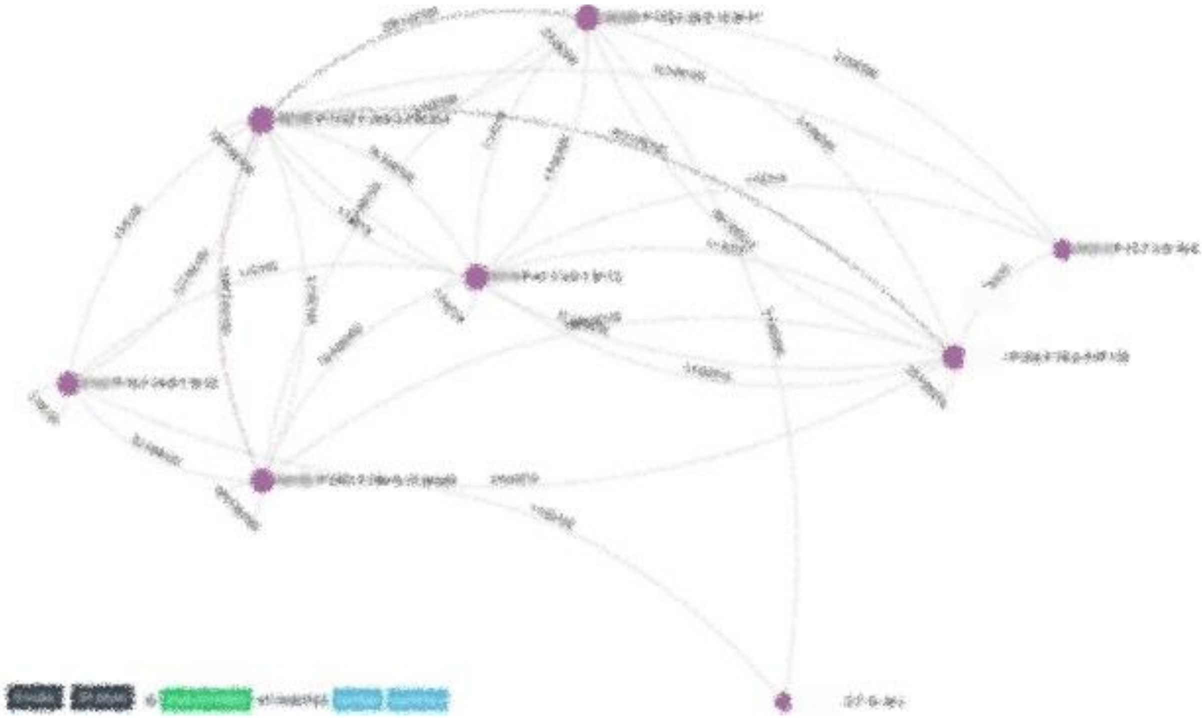
2.3 Findings

2.3.1 What choices do students make after A05 in their subsequent study?

This is an exemplar that answers the more generic question: how can we tell what a particular cohort of students goes on to study after taking an initial module-presentation? To answer this question we need to select all the students within the defined cohort, and for each student identify their subsequent study choices. These data can then be summarised using a series of queries similar to the one shown above. When we did this we found a diverse range of study routes taken by students who started their studies with the A08-2014J module-presentation. Several of these routes have very few students. While this can be presented as a table, and output, it is an example best summarised through a graphic plot, as seen in Figure 2.1.

Figure 2.1 displays each of the modules as a node and the edges connecting the nodes show how many students who passed one module go directly on to the other. In addition, figures have been added to the nodes and edges, and the edges are colour coded depending on the number of students they represent. We have enlarged a section below in Figure 2.2. In this diagram, the node is for A05 and shows that from the sample data set, a total of 2401 students who attempted 2014J eventually passed the module: 180 are shown to have looped directly back onto A05, either through failing, deferring or withdrawing from the 14J presentation. The three other edges within the figure show some of the less popular study route choices, with for example, 2 students who started with A05-14J coming back to A05 after passing A10. The purple edge indicates more than 1000 students and is to A09, the main study choice (in our data) after passing A05.

Figure 2.1 Subsequent study for the 2014J cohort studying A05, from a sample dataset



The text by the node gives numbers of students from the 2014J cohort **P**assing (2401), **F**ailing (780); **D**eferring (10) and **W**ithdrawing (669) from A05. The interconnecting lines give the number of students moving directly between modules, with the 'f' indicating which module they are coming from - as there are no arrowheads. The thicker purple line is coloured to show the number is greater than 1000 (this can be set by the user). We can see the vast majority (1549) then go to A09. From here, we can see the majority then go to study A10 (412), and second most popular is A06.

The numbers decrease considerably through the progression of modules: if most study at a rate of one 60 point credit module per academic year we might expect a larger proportion of students who started with A05-2014J to progress past their third module at the time of sampling (November 2017). However, we must remember this is a sample data set and does not necessarily show all the study of the selected cohort: they may have studied outside of this group of modules. This visualisation may be used to explore questions that can then be explored further.

We restricted our sample data set to students studying within the 'new regime' and as time progresses, we will gain a more complete picture of student progression over a whole qualification. However, over these longer periods, it may be that the module options for students on a qualification change, with older modules being retired and new ones becoming available. This may mean that analysis using data from the older modules is less relevant to Faculty and suggests there is a time-slice (potentially programme dependent) which is optimal for analysis.

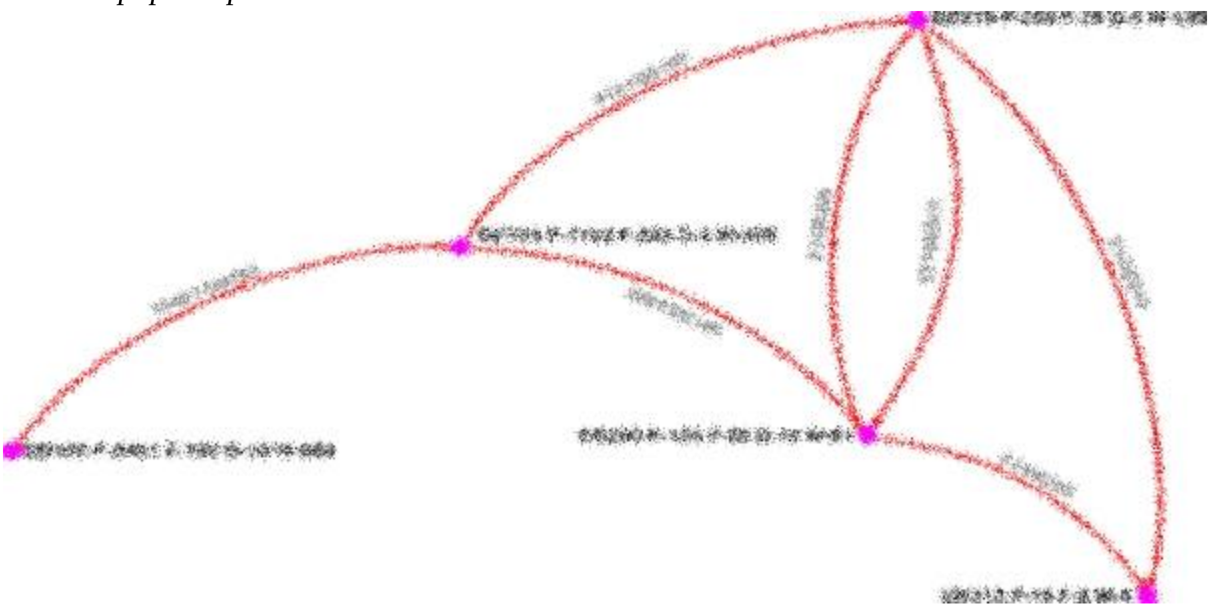
Figure 2.2 Zoomed in subsequent study for the 2014J cohort studying A05

The text by the node gives numbers of students from the 2014J cohort **P**assing, **F**ailing; **D**eferring and **W**ithdrawing from A05. The interconnecting lines give the number of students moving directly between modules, with the 'f' indicating which module they are coming from - as there are no arrowheads. The thicker purple line is coloured to show the number is greater than 1000.

2.3.2 What are the most common sequences of routes through the QUAL1?

The graphs in ArangoDB are interactive. It is therefore straightforward to drag the nodes around on-screen to make the most popular paths taken by the selected cohort of students more visible. Figure 2.3 is a portion of the same graph as in Figure 2.1 but has been rearranged to make the largest flows of students more visible. The numbers of students in each column do not total the previous total for several reasons, including: some students may have paused their study; some students may have studied modules not included in the sample dataset; we are only looking at the top one or two (based on numbers) transitions at each step, and are therefore excluding those making other choices.

Figure 2.3 Subsequent study for the selected cohort (A05 14J), rearranged to better show just the most popular paths



The Figure 2.3 and Table 2.1, can be easily read and together with the graph can help focus discussion on the effectiveness and health of the programme. At the moment, this graph contains the data for all students within the A05-14J cohort. Depending on the question this can be refined to reflect study intention, educational background or any combination of values of the variables within the dataset.

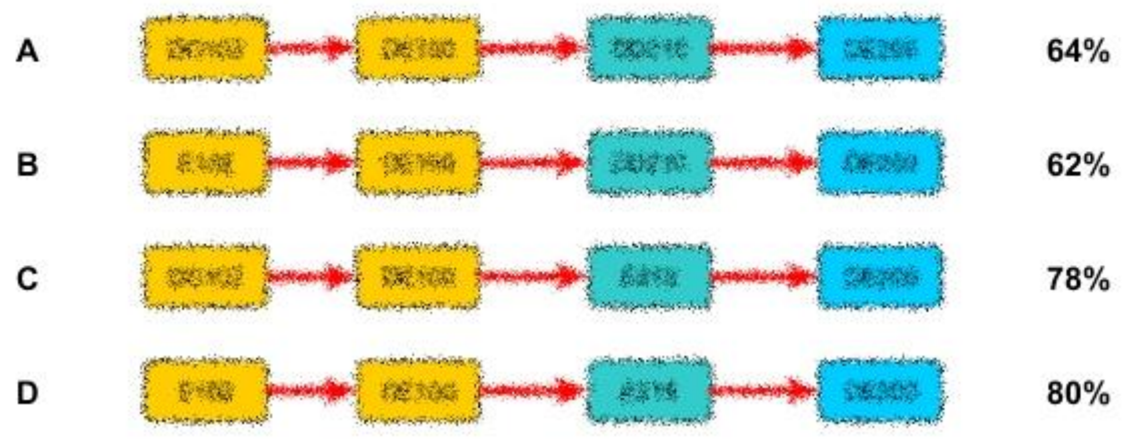
Table 2.1 The numbers of students from the A05 14J presentation passing one module and going directly on to study the next module

A05	1549	A09	412	A10	63	A06	2	A11
			206	A06	2	A10	5	

2.3.3 Transition from one module to the next

Our third question explores the successful pathways that students might take. For example, does one Key Introductory module (A05 or A07) better prepare students for the second level compulsory module A06? i.e. are students who take and pass A07 more likely to pass A06 than those who take and pass A05? There are four main study routes within the QUAL1 degree, to A06: the compulsory module at the end of Level 2 study. They are shown in Figure 2.4. Using a simple query, we can consider just those students who studied just the modules in each of the four study paths, A - E, in the order specified. and compare the relative pass rates. The resulting pass rates are shown in the last column in Figure 2.4.

Figure 2.4 Four study routes through the QUAL1 programme of study to A06 - A to D.



Note: The final column of figures are the percentages (against R25 values) of those passing A06 for each study route. Only students who declared their qualification intention was QUAL1 were included from the sample dataset

From the sample dataset, it would at first appear A12 is a better precursor to A06 than A10 for students aiming for a QUAL1 degree. There is certainly a marked difference in the pass rates. However, as highlighted in Table 2.2-2.3 there are markedly fewer students studying routes C and D than A and B. Other demographic factors may also be involved, and a fuller analysis would be necessary, and this is aided by each query returning the student data as well as the total numbers (Rienties, Rogaten, et al., 2017). It should be stressed that whilst only the figures have been reported here, each query returns the data for the students, not just the total. This data can be used for a more complete statistical analysis.

Table 2.2 All those following the paths A-D, irrespective of qualification intentions

Study path	Pass A06 (of R25)	Fail A06 (of R25)
A	77 / 120 = 0.64	7 / 120 = 0.06
B	41 / 64 = 0.64	3 / 64 = 0.05
C	14 / 18 = 0.78	0 / 18 = 0
D	34 / 44 = 0.77	5 / 44 = 11

Table 2.3 All those following the paths A-D, who declare a study goal of QUAL1

Study path	Pass A06 (of R25)	Fail A06 (of R25)
A	36 / 56 = 0.64	4 / 56 = 0.7
B	38 / 61 = 0.62	3 / 61 = 0.05
C	14 / 18 = 0.78	0 / 18 = 0
D	31 / 39 = 0.80	4 / 39 = 0.10

2.4 Conclusion

There has been a longstanding challenge to provide greater access to data on curriculum effectiveness and student experience beyond a single module. The challenge existed before the current funding regime, introduced in 2013. Since this change the need to more readily prepare extended study data for analysis - in order to check the effectiveness of qualifications, programmes of study and the effects of student choice on experience - has become more pressing. Colleagues have, over the years, shown the data can be queried to produce responses to specific queries and SIO are currently finalising a progression dashboard[9] that will give the status based on several indicators. We have described a complementary approach that enables the rapid querying of data to facilitate analysis of both simple and complex questions relating to study choices and routes. Whilst the progression dashboard will focus on providing consistent comparative data on a set of Institutionally agreed indicators, this work will enable a wide range of research and development questions to be readily put to the data and increase support for curriculum development and the enhancement of the student experience.

This development work has provided proof of concept that a graphic data structure can make pathway related patterns in the data more readily accessible, and make that data available for further analysis. Having produced this cohort analysis group of queries, work is ongoing to expand the ‘library’ of queries that can then be used by others, and adapted to purpose. For

[9] http://intranet6.open.ac.uk/strategy-and-information-office/what-we-do/strategic-planning/institutional-performance

example, there has been Faculty interest in exploring the hypothesis that students who are overlapping or concurrently studying multiple modules are impacting their success rates compared to the general cohort progressing towards a qualification[10], and we are turning to explore this hypothesis. This is possible because as part of the data preparation, each students' study is analysed programmatically to produce the 'edge' information for the database. One of the steps in this preparation calculates the time between a student beginning one module, and when they start the next. Where this value is zero, a student begins two or more modules at the same time: concurrent study. Where the value is greater than zero but less than the duration of the first module, there is some overlap.

In the first instance this work was driven by the need to respond to several ad hoc requests from Faculties, and as we fulfil these it will enable us to test the efficacy of this approach. Whether it might be more widely adopted beyond the piloting team to other Data Wranglers and those members of OU Faculties interested in exploring and manipulating data in such a platform. Future research questions to explore could include:

- How do students following a particular named path on the Open Programme compare with other paths, or with the students following the same series of modules but with another named degree as their declared study goal?;
- In what sequence are students studying modules most frequently? Do they tend to do all of language 1 from stage 1 to 3 before doing all of language 2, or do they study stage by stage, or a mix?

[10] See https://openuniv.sharepoint.com/sites/qual-enhance/test-learn-evidence/Pages/Concurrency%20of%20studies%20impacts%20pass%20rates.aspx

3 ANALYTICS4ACTION REVIEW OF EVIDENCE: THEMES EMERGING FROM THE PROCESS AND CASE STUDIES RELATING TO ADOPTION OF NEW APPROACHES

Highlights

1. Analytics4Action stimulates OU colleagues in module production and module presentation to work together and to explore more active use of data, and where possible provide actionable insight and intervention.
2. Four substantial trends were identified when working with 29 module teams: workload issues; knowledge or skills gaps; retention issues, and community and collaboration difficulties.
3. Several clashes and overlaps were identified in TMAs between concurrent modules.
4. Eight modules had concerns about student isolation and the collaborative elements of the module
5. Three case studies show how the learning analytics available for an individual presentation of a module can lead to effective support in teaching and learning

3.1 Introduction

In 2014 the PVC LT initiated a learning analytics innovation programme, whereby one of the pillars within this programme was called Analytics4Action (A4A). In A4A it was envisioned that OU colleagues from a range of disciplines and units would work together to explore more active use of data, and where possible provide actionable insight and intervention in or after a respective module presentation. Building on the initial positive findings and encouraging support from OU colleagues on the A4A approach (Herodotou et al., 2017; Rienties, Boroowa, Cross, Farrington-Flint, et al., 2016; Rienties, Boroowa, Cross, Kubiak, et al., 2016), the A4A approach was moved into business as usual in 2016/17. This applies an analysis across findings and actions for all of the modules in scope to identify the core themes being raised as issues by module teams (Evans, Hidalgo, & Calder, 2017; Hidalgo, 2018). This builds on a recent Quality Enhancement report on A4A (Evans et al., 2017) and so does not explicitly cover the A4A process, the report here should be read in conjunction with that report for a full understanding of process. The aim here is solely to report back findings. Following on from this are a series of case studies of A4A work by the team.

The aim of this Chapter 3 is twofold:

1. To outline the types of issues being encountered in the real world for OU module teams when they look in depth at the data relating to their modules
2. To provide some examples of using the data to look more in depth at the issues and to understand approaches to potential actions

In 2016/17, TEL Design supported 29 module teams[11] with review through use of the A4A process. Having completed this year's work the team are now able to report back on themes coming out of the work alongside some of the most interesting case studies from the modules in scope. In this Scholarly Insight report we will report back on the themes identified from the 2016/17 A4A round, which relate to workload, knowledge and skills gaps, retention issues and community and collaboration difficulties. There are some particular threads here which will need to be addressed by the OU in our move toward a new teaching framework if we are to better enable students to succeed in their studies.

Following this, Chapter 3 will look at case study examples from A4A of how TEL Design have supported module teams in introducing innovative approaches in their module and the analysis work carried out as part of A4A to review their effectiveness. These provide a strong example of how we can go about innovation in our curriculum and measure the effectiveness before committing to any further scaling up of the approaches. The use of learning analytics is playing a key role in enabling these discussions and findings from a cross-section of modules and provides a strong evidence base for us to move forward from.

3.1 Themes from 2016/17

From 2016/2017 modules selected by their faculty to be part of the A4A process were offered a supported route through the data with a faculty-facing Senior TEL Designer (STELD). This supported route took the form of three data support meetings during presentation: the first meeting took place after the first TMA, the second at a suitable mid-point in the presentation and the third, four weeks after the module has finished. The A4A meetings themselves focussed on the visual data presented in the Student Progression Dashboard and were an opportunity for STELDs and module teams to examine the data and contextualise the findings via qualitative feedback.

By involving module chairs and curriculum managers in a guided process for interpreting data, the A4A process harnessed both quantitative data and qualitative feedback that module teams had access to via module forums, Associate Lecturers (ALs), Student Support Teams (SSTs), Student Experience on a Module (SEaM) survey results and so on. From a qualitative analysis of the meeting notes and findings, four broad themes were identified that may have potentially hindered student engagement or impacted on student retention. Sometimes these were issues known to the module team, sometimes they were identified by an analysis of the data; usually the findings were a combination of both these elements. These themes and their sub-themes will be set out in more detail later but in summary they were:

- Workload issues
- Knowledge or skills gaps
- Retention issues
- Community and collaboration difficulties.

[11] 29 module codes blinded

As illustrated in section 3.2, these themes provide us with a picture of the challenges individual teams are facing once their module is up and running and some of the key areas we need to address as we move forward. The 2016/17 A4A modules also provide some examples of how we have used the available evidence from the learning analytics and provided support to the module teams and to students.

3.2.1 Workload

TMA clashes

Using concurrency data from the dashboard, examined during data support meetings, we investigated how many of the modules being studied concurrently by students had TMA deadlines which fell within the same week. The data for nine modules exposed a high number of students with such TMA clashes for their concurrent modules. In addition to planned deadlines falling within the same week, there were in some cases extension policies which would mean TMA deadlines would clash following an extension.

Table 3.1: TMA submission deadlines for social sciences level 1 modules (clashes with A05 shown in red)

Week commencing	A05 16J	A09 16J (341 students)	A13 16J (36 students)
17/10/2016	TMA01 20/10/16		
31/10/2016		TMA01 01/11/16	TMA01 01/11/16
14/11/2016	TMA02 17/11/16		
28/11/2016			TMA02 29/11/16
19/12/2016		TMA02 20/12/16	
02/01/2017			TMA03 05/01/17
09/01/2017	TMA03 12/01/17		
20/02/2017	TMA04 23/02/17	TMA03 21/02/17	TMA04 21/02/17
10/04/2017		iCMA41 11/04/17	
17/04/2017	TMA05 20/04/17		TMA05 18/04/17 iCMA41 21/04/17
24/04/2017		TMA04 25/04/17	
22/05/2017	EMA 25/05/17	EMA 23/05/17	EMA 24/05/2017

Note No of students studying concurrently with A05 16J

The impact of TMA clashes is demonstrated by A05. Table 3.1 shows a comparison of the TMA submission deadlines for A05 2016J with A09 2016J and A13 2016J – these were the two modules that A05 students studied concurrently in the highest proportions (341 students and 36 students respectively). Clashes and therefore workload is particularly high around the mid-point of the modules and at the EMA submission deadlines. The advice from van Ameijde, Weller, and Cross (2016, p. 7) to "look for potential blackspots and address these" is something that needs to be applied at a qualification as well as a module level.

For example, A14 expressed a concern in relation to managing TMA clashes as most of their students are registered on an Arts qualification, but their module is run by FACULTY4. This is likely to be an issue for other modules where responsibilities are spread across Faculties. Even when TMA clashes are planned for, A15 explained that planning was disrupted by frequent extensions to submission dates. A close monitoring and link between the module team and ALs is needed to look out for any clashes which might have been inadvertently built in, but also to respond with effective TMA extension strategies that don't then create further assessment clashes. Recent work by LTI on longitudinal comparisons of assessment practices have highlighted similar concerns, whereby a vast difference in assessment practices and timings of assessments were identified (Cross, Whitelock, & Mittelmeier, 2016; Nguyen et al., 2017; Rienties, Lewis, McFarlane, Nguyen, & Toetenel, 2018; Rienties, Rogaten, et al., 2017). Furthermore, a fine-grained analysis of when students actually studied for their assessments showed that most students study at substantially different time intervals for their respective assessments (Nguyen, Huptych, & Rienties, 2018), thereby potentially encouraging a stronger need for clear assessment times across modules. Therefore, modules within and across qualifications need to work together to at least raise awareness of potential clashes in assessment timings between common concurring modules. While in an ideal world assessment patterns should be aligned between modules, in practice raising awareness of potential clashes to Associate Lecturers and students might mitigate some of the workload and assessment issues.

Concurrency and employment

Ten modules were concerned with concurrency rates for their modules. Concurrency is when students study more than one module at the same time. The data showed that a high number of their students were studying 120 credits or more. This seemed to be a particular issue in FACULTY2, where there were high numbers of students with heavy workloads and high numbers in full- or part-time work.

For example, 89% of students registered on A16 2016J were studying 90 credits. In addition, 32% of students were working full-time and 29% of students were working part-time. From this we can assume that a high proportion of students for this module had a heavy workload in relation to their lifestyle. The module team did not feel that intervention was needed here and that it was the norm for motivated Law students who were keen to complete their degree. In fact, pass and completion rates for A17 and A16 were both above the Board of Study averages, belying our expectations that a higher workload would have a negative impact on student outcomes. Previous research involving interviews with 12 module team chairs revealed a perception that there is a negative correlation between average weekly workloads and student outcomes (van Ameijde et al., 2016). The finding on A17 and A16 illustrates that there are occasions where this negative correlation is not witnessed.

Other workload issues

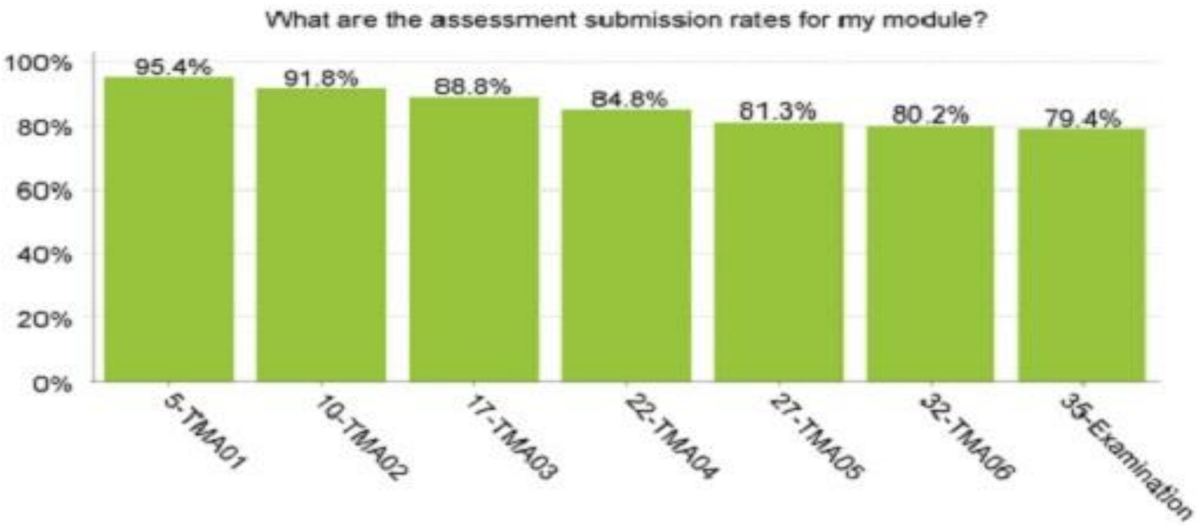
There were a few other issues relating to workload which did not quite fit into the subcategories above and they are worth mentioning here. For example, feedback from tutors on A18 indicated that the module had too many forums. The data showed that engagement was low overall on the forums, in addition to this there were at least three not linked to subject areas: Café, General, Welcome. This is not an ideal use of forums as Pinchbeck (2012, p. 2) explains that "research into online learning communities showed that it is the participation in the learning activities that creates and maintains the community rather than the online community emerging first.". For example, A19 data showed that TMA 03 extensions delayed engagement with exam preparation, evidenced by late student engagement with relevant online resources and requiring the module team to send reminder emails to students. This late engagement is likely to impact on student pass rates as "sufficient time for revision and reflection before assessment points" should be built in (van Ameijde et al., 2016, p. 6).

3.2.2 Knowledge or skills gaps

Gaps in material

Five modules expressed concerns about 'jumps' in difficulty of material. In the first data support meeting A18 anticipated that the difficulty of TMAs 04 and 05 might cause a reduction in assessment submissions, as indicated in Figure 3.1. The second meeting confirmed a slightly steeper drop in submission rates between TMAs 03, 04 and 05. Despite this, submission rates held well throughout the module with a TMA 06 submission rate of 80%.

Figure 3.1: A18 2016J TMA submission rates (Students registered at 25% FLP)



Gaps in student knowledge

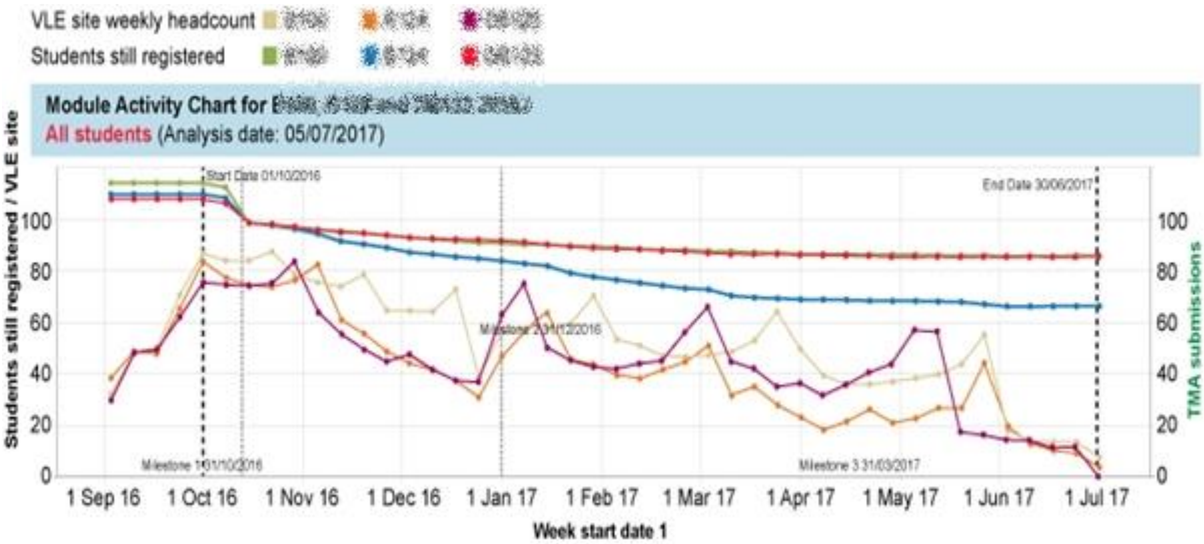
Eleven modules either reported concern about students' preparedness for the material or had a higher number of students with lower than A-level PEQ when compared with the university average. For example, the A20 module team were worried that students were not prepared for the more technical nature of A20 compared with other modules in FACULTY2 at level 1 (A21 and A22) and that this might be the reason for the comparatively higher withdrawal rates, as illustrated in Figure 3.2.

The A14 module team were already aware of possible gaps in student knowledge and came up with a strategy to deal with this. The module team recorded a series of screencasts in order to tackle gaps in student knowledge. Positive comments from students show that these screencasts had been very well received:

“This is massively useful. It's just exactly the kind of thing that is needed” (Student 1 A14 2016J)

“This is great, as I am dyslexia [sic] and struggle with the amount of material to read.” (Student 2 A14 2016J)

Figure 3.2 A20 retention rates compared with A21 and A22

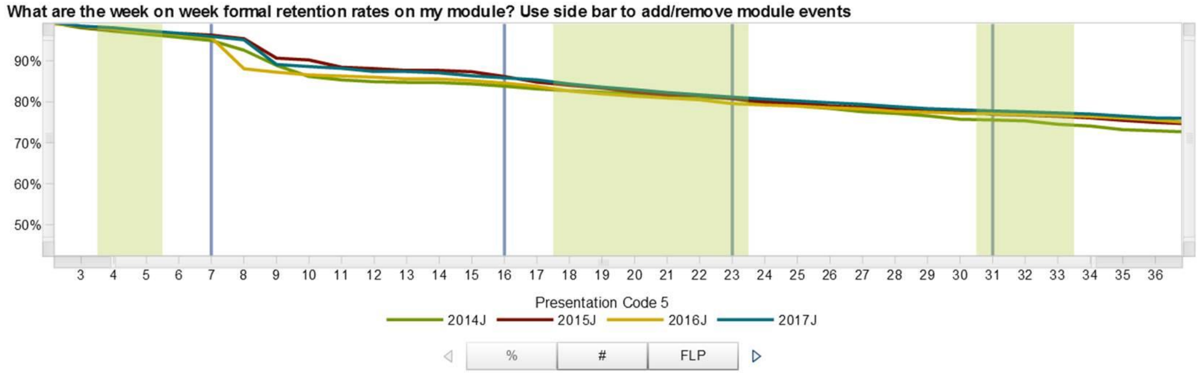


3.2.3 Retention issues

Funding

Four module teams were concerned that funding was affecting retention. A wider investigation into rates of withdrawal has shown a steep drop **between weeks 7 and 8** across a high number of modules (see Figure 3.2 above and Figure 3.3 below). Following further investigation, it was found that if students had not paid after 28 days from module start they were given a ten-day grace period in which to pay. If payment was still not received, they would be deregistered by the OU and their access to the VLE removed. This lack of payment was usually due to funding from the Student Loans Company not being in place. A change in policy in 2014, required students to have an approved payment in place by day 14 of the module. Figure 3.3 shows that bulk de-registration followed a very similar pattern in the 2016J and 2017J presentations, only a week apart due to Module starting in a different calendar week. There is no further evidence of this practice having an impact on overall retention figures.

Figure 3.3: Formal withdrawal rates on A07



Group tuition policy

Seven modules referred to group tuition policy (GTP) playing a role in student numbers dropping – something that had been reported to them by ALs, and was also highlighted in Chapter 1. A23, A24 and A25 felt that GTP issues had resulted in lower TMA submissions.

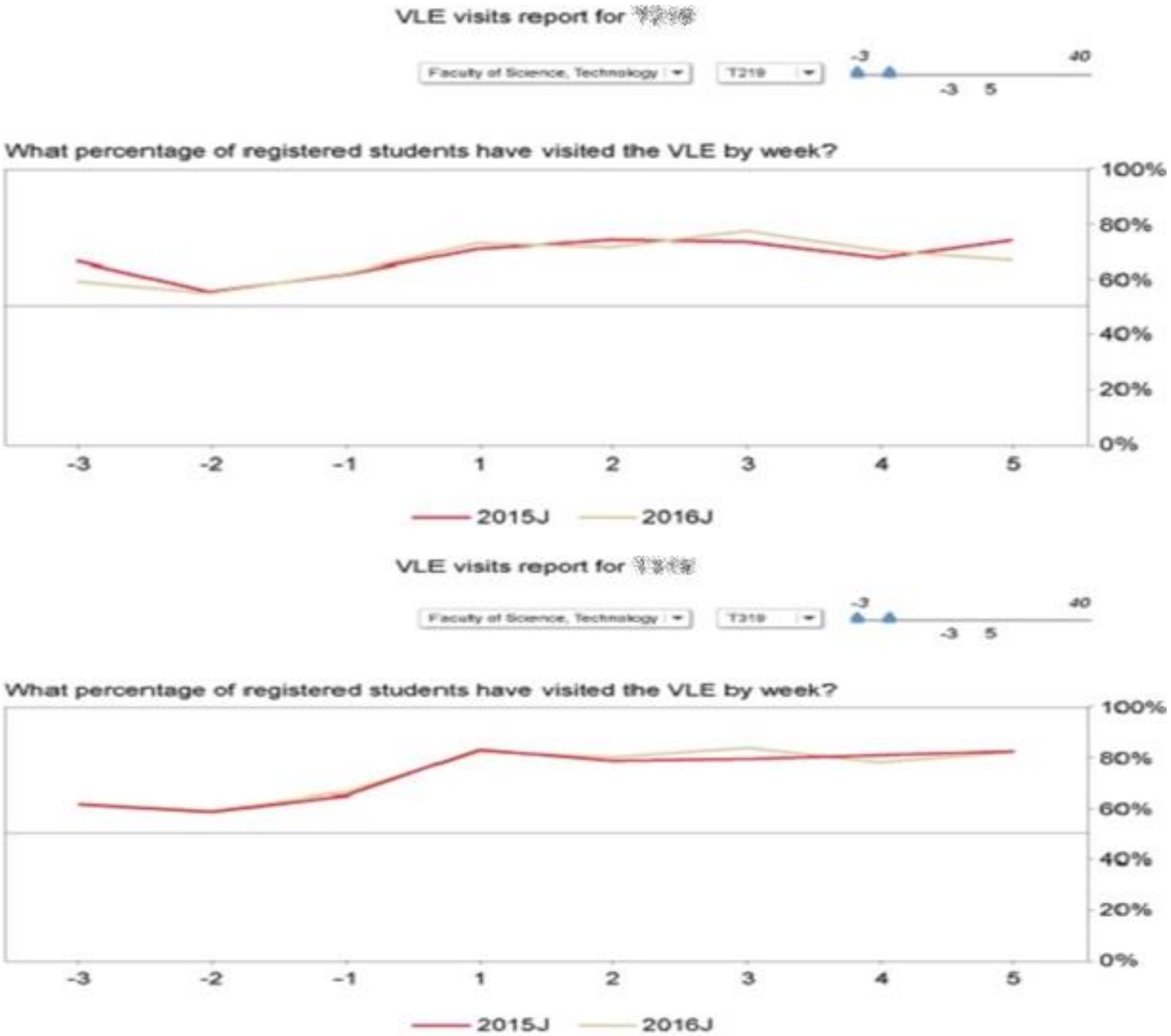
Investigating this further, for A23, TMA 02 submission rates did drop significantly between 2015J and 2016J. For students registered at the time of the TMA submission date, 91.3% of students submitted TMA 02 in 2015J compared with 85.8% for 2016J. As A24 and A25 changed their TMAs between 2015J and 2016J any impact is more difficult to identify.

Having an awareness of such changes in policy and recognising these in conversations with ALs and students is important in providing support to students during presentation, but as the data above show it's not immediately clear that this change in itself had a significant impact across the board on student engagement.

VLE issues

Three modules reported that unavailability of the VLE (or materials on the VLE) had affected retention. Further investigation into the data showed that the unavailability of the VLE on 3 and 4 October 2016 (approximately around Week 1 in Figures 3.4) did not alter the percentage of visits to the VLE when 2015J and 2016J were compared – and that the two modules showed almost identical interaction patterns.

Figures 3.4 A26 and A27 Pattern of students' interactions with the VLE in 2015J and 2016J (Weeks -3 to 5).



3.2.4 Community and collaboration difficulties

Eight modules had concerns about student isolation and the collaborative elements of the module, but these concerns were very mixed. Many conversations centred on advice from STELDs about the best way to set up and run collaborative activities. This advice was based on previous research undertaken in TEL design (Evans & Galley, 2016). It included keeping OpenStudio open for the duration of the module, ensuring that students understood the benefits of collaboration and increasing engagement by assessing collaboration.

3.3 Case studies

In the remainder of Chapter 3 we will explore three case studies how the learning analytics available for an individual presentation of a module have been utilised in the 2016/17 A4A process. The first case study, A28, shows how the analytics provided a view on how well a module design was working. The second, A14, provides an example of the supportive nature of the A4A process for staff new to the process and to working with learning analytics. Finally, A15 shows how analytics enabled action to support students studying modules concurrently.

3.3.1 Case study 1: A28 16J

What does this show: how to use data to monitor design features

An example of how we used data from different sources to verify assumptions and monitor student engagement with design features in a new module.

Background

A28 is an entry Level 1 module in Faculty3. It replaced a previous module – A29- which has come to the end of its cycle with remarkably good feedback on Study Satisfaction terms but not so good pass and completion rates. A29 was designed as a print-led experience with a fair proportion of interactive assets.

The A28 module team was given the challenge to design a completely online module that replaced A29, improving student outcomes and registered student numbers, while keeping high levels of student satisfaction. All new students pursuing a Science degree are expected to take this new module. The A28 team responded to the challenge by designing an all-digital activity led module, with a number of two weeks cycles lead by a single question (for example *"Is there life on Mars?"*), in which content was brought to help students find an answer for the question. As well as gaining knowledge in sciences through the topics, A28 students develop study skills, maths, practical skills and PDP and employability skills. A28 has the crucial role of preparing students to become independent learners.

Two of the premises for the module design were that a) building a sense of study community will increase student engagement and hence improve student outcomes and b) that a continuous assessment only strategy would result in higher assessment submission rates - particularly towards the end of the module - and better student outcomes. In order to provide and foster the sense of community, the Module Team used a number of strategies, including a Live Debate on a module related topic open to all students, a dedicated Twitter account and the use of the standard VLE tool Open Studio, among others. Regarding the assessment strategy, it was agreed to closely monitor the submission rates from the beginning and take actions to minimise withdrawals at late stages.

Using data, what we measure and how did we measure it?

Live Debate

Student on-line engagement with the Live Debate was measured using a variety of parameters and tools, including the unique viewers of the live video feed, the number of active unique users via the chat, the interactions through the Twitter account and the number of interactions with the map app, showing the places the users were at during the event. The data showed 174 unique viewers and peak of 150 concurrent viewer with an average viewing time of 36m26s. Interactions after the event were also measured, with a total of 410 unique viewers watching the recording and an average viewing time of 25m32s in the first three weeks after the event. In addition over 50 people attended in person – 35 of them registered as A28 students- to the event, bringing our estimate of direct participation to 39% of the registered students at the time of the event. Considering that the event was non mandatory and not assessed, this level of participation (out of 1198 students registered at 25% FLP) is considered to be very high.

The Twitter account

For monitoring engagement with the Twitter account we used the built-in Twitter analytics. We classified tweets into different categories and measured the interactions with each type of tweet, as indicated in Figure 3.5. The engagement rate is calculated as the proportion of the total number of interactions (engagements) compared to the total number of opportunities to engage (impressions) as defined by Twitter Inc. With this information we informed the next presentation (17B) about the student preferences. Tweets that were aimed at building communities were the most popular. At the end of the module we conducted an online survey capturing the opinions of students about the Twitter account. The success in A28 led other modules such as A30, A31, A32 and A33 to launch a Twitter account using the findings from A28.

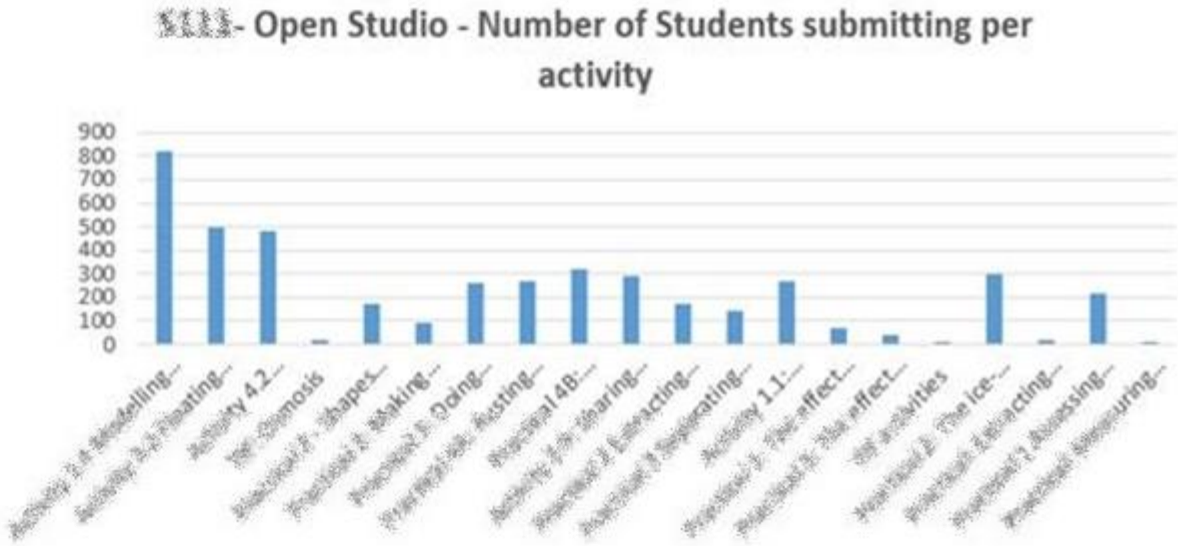
Figure 3.5 Types of tweet on A28-16J and student engagement with each type.

Type of tweet	Impressions	Engagements	Engagement rate	Tweet type total	% tweets total
Tweet chats	28,800	1,158	4.0%	74	15.7%
Promotion	20,165	658	3.3%	52	11.0%
Interaction	44,794	1,426	3.2%	180	38.2%
Content	45,651	1,085	2.4%	123	26.1%
Module Activity	14,955	297	2.0%	42	8.9%
ALL	154,365	4,624	3.0%	471	100%

Open Studio

A28 also uses the standard OU VLE tool "Open Studio" as a way to facilitate sharing among students of their individual work. Students are asked to publish the results of their experiments and are encouraged to comment on others' work. By monitoring the response – using the Open Studio own report usage- from students to the different activities we are able to inform future presentations on student engagement with each type of activity. As illustrated in Figure 3.6 we can see that some activities are being well engaged with, others have very few students participating. This will be reviewed with data from the next presentation and any adjustments will be made where deemed necessary.

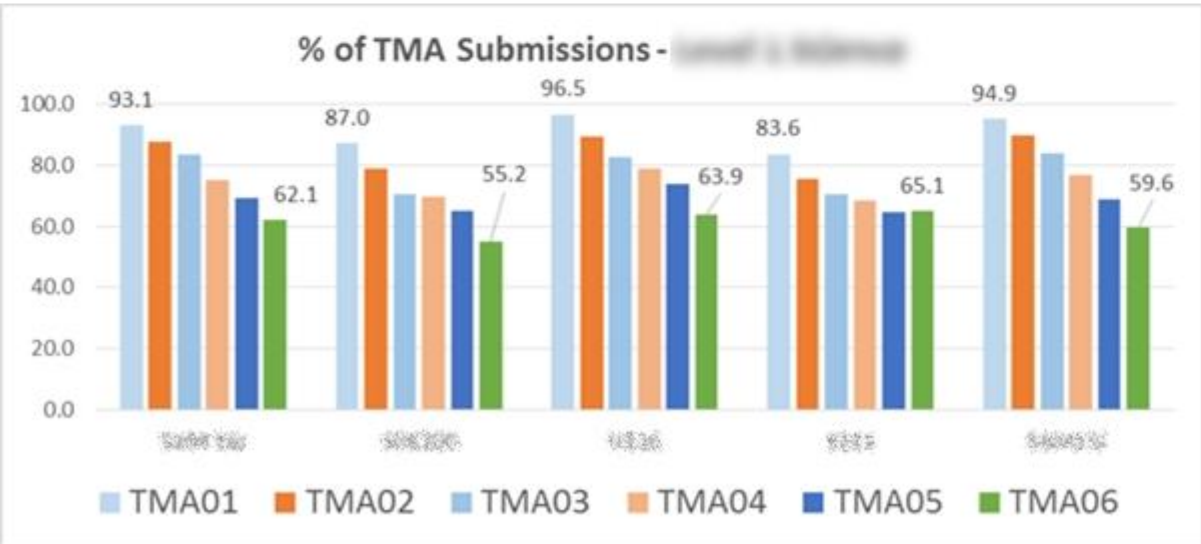
Figure 3.6 List of some of the OpenStudio activities on A28 and student engagement with each.



Assessment strategy

The assessment submission rates were closely monitored via the Student Progression Dashboard. Students were reminded about upcoming deadlines via the VLE site and also through the Twitter account. The submission rate for TMA01 was below expectations, in fact lower than all other similar modules. The Module team used VLE engagement data and assessment data to engage appropriately with students via SST and/or via ALs to encourage further study or intervene when required. By the time of the last TMA, the submission rate was the best of the comparison group, as illustrated in Figure 3.7. The same outcome has been reported for A28 17B.

Figure 3.7 A28 TMA submission rates compared with 4 other level 1 modules in FACULTY3



Student outcomes

Final pass rates for A28 outperformed all but one of the comparison modules -including A28 predecessor - while keeping very similar satisfaction rates. By continuously monitoring the available data the Module Team was able to assess how design features were contributing to student engagement and this insight was used drive changes in the current and later presentations. In addition, the work on Twitter has driven best practice in designing in Social Media approaches as part of teaching, with other modules in FACULTY3 such as A30, A31 and A32 having launched their own Twitter account followed the principles tested in A28.

3.3.2 Case study 2: A14 16J

What does this show: the supportive nature of the A4A process

Background

A14 *Language and creativity* was a new FACULTY4 60-credit module for 16J. It runs over 32 weeks, comprises four TMAs and an EMA with a combination of online and print content, the module website driving the student journey through the Study Guides (Figure 3.8). Due to the fact that A14 was being supported in its first year of presentation, the Module Chair was wary of making too many changes so as to be confident about what the data was saying. Also because the data support (A4A) process was in its infancy, the Module Chair was not fully convinced the A4A process would deliver and that it may simply become a bureaucratic process which historically has sometimes been the case at the OU. Nevertheless, we held three data support meetings with the Module Chair, Curriculum Manager and two Senior TEL Designers, Sue Lowe and Beccy Dresden, over the course of the presentation. The agendas were open for the Module team to feed into and consequently each meeting was tailored to their requirements.

Figure 3.8 The online-offline design of A14

Block 1: Creativity in language	Block 2: Narrative, language and creativity	Block 3: The politics of language and creativity in a globalised world
Study Guide 1	Study Guide 2	Study Guide 3
Book 1	Book 2	Book 3
Study planner		
Set book (*Stylistics*)		
Audio-visual materials		
Study skills activities		
English: A Linguistic Toolkit		

The experience

The impact of concurrent study (Figure 3.9) and extensions to TMA submissions (Figure 3.10) was a main theme for the three A4A meetings, alongside potential skills/knowledge gaps particularly for students studying A14 as part of the Open Degree. However, this case study focuses on the experience of the data support provided by TEL. The Module Chair by the end of the data support process appreciated being able to look at her module alongside other modules in the curriculum area to see if there were any differences between them or year-on-year changes for a particular module.

The Chair also appreciated being able to go 'off grid' and finally (her words) get some insights and answers into presentation questions module teams have had for ages. This is what she found the most valuable working with the Senior TEL Designers, the fact that Sue and Beccy were familiar with FACULTY4 and with A14, and were familiar with the way in which modules are designed and produced. The Chair made a plea that the A4A process remains open in this way so as to be able to answer module team questions which can't always be answered by other processes. The Chair found the context of proper discussion (her words) particularly useful.

Figure 3.9 Number of students studying another module besides A14_16J

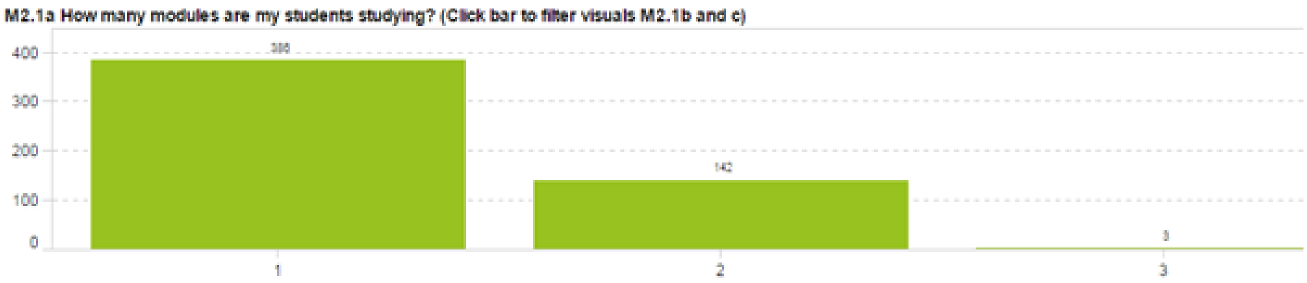
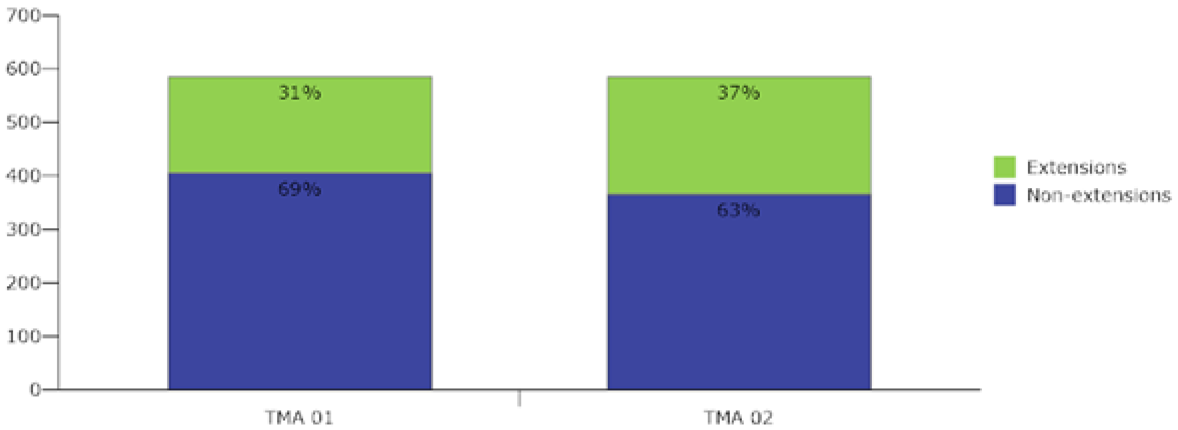


Figure 3.10 Number of extensions on the first assignments in A14_16J



Findings and actions

While the number of students studying more than one module may have been less of a surprise, the volume of TMA extensions on A14 –and in general – was a big surprise for the Module Chair and this is being taken up by the chair in the AQR process, a particular challenge being that students can request extensions via their SST as well as via their tutor. In order to support students in general – as well as those who may have some gaps in skills/knowledge, potentially those on the OpenDegree – the Module Team were already creating their own screencasts and they will continue to do this given they were well received by students. The module team, along with A04, made them available via welcome forums, tutor group forums and News. In order to enhance TMA submissions as much as possible, following the data support meetings, there were plans to develop a screencast around using tutor feedback.

3.3.3 Case study 3: A15 16J – Evaluating contemporary science

What does this show: Understanding and acting on concurrent study information

Background

The A15 module team designed the module to be delivered entirely online, with assessed collaborative activities using online rooms, Open Studio and forums. There is a focus on developing skills in data analysis and presentation skills. The content takes the form of a number of topics around which student skills are developed. The module is interdisciplinary with students having a range of background subject areas. It is a core optional module in the Chemistry, Earth and Environmental Science pathway of BSc Natural Sciences, BSc Environmental Science and BSc Health Science as well as the Open Degree.

A15 was included in A4A due to its use of the new VLE design (Online Student Experience), use of innovative technology (the inclusion of RShiny for the visualisation of statistical datasets in student activities) and its multidisciplinary approach. The module team meet with TEL Designers in LTI three times during presentation to review the data available on the SAS VA Institutional Dashboard to identify areas of success and concern or opportunities for real-time intervention.

Data and concurrency issues

The first data support meeting was held on 12th January 2017, involving the module team chair, curriculum manager, and two members of the TEL Design team. This was four weeks after the first TMA submission date. Information on the SAS VA Dashboard was looked at to review the characteristics of the student population, reflect on student engagement at that point in time and be able to compare this data to retention later on.

One of the key findings concerned the high proportion of students studying another module at the same time as A15. When 17B modules were taken into account, the concurrency levels were 73.4%. Early evidence around student engagement was positive with the TMA01 submission rate at 95.3% and only 2.3% (7) students had withdrawn since Fee Liability Point (FLP 25). However, with 75% of A15 students being employed, and 50% of the total cohort in full-time employment, there was concern about the impact of high study intensity for students studying multiple modules.

Concurrency was an expected issue for the module team and they had coordinated with other modules to avoid clashes in assessment dates. Extensions to TMAs can disrupt this timing. The order in which students choose to study modules is also something that can’t be controlled. For example, students are advised not to take the A34 project modules before passing A15 but in practice many are doing so.

Action

Due to the concurrency issues being identified through the A4A process the module team had the opportunity to intervene at an early point in the module’s presentation. The high workload of specific students was flagged to their tutors along with the assessment dates of the three most likely concurrently studied modules so that they could be careful when allowing TMA extensions that could lead to clashes. Using the data held on participating users on the VLE module site the module team were also able to identify students who had not visited the site within the 10 days prior to the last TMA submission date, and flag this to their tutors.

Evaluation

Whilst there was no previous presentation to compare the actions above with, the proactive approach to talking with students and tutors was largely enabled by the learning analytics available within the OU systems. This close liaison and support for the students is a clear example of how we as an institution can personalise our support to individual students.

3.4 Conclusion

The themes and case studies are presented here to cover two aspects:

1. The types of issues being encountered in the real world for OU module teams when they look in depth at the data relating to their modules
2. To provide some examples of using the data to look more in depth at the issues and to understand approaches to potential actions

This two-fold approach is aimed at showing firstly that there are significant issues we encounter when looking at the data on our modules, and secondly that the data can be used effectively to delve into this and to identify and prioritise often very simple actions that can help to keep students on track.

The themes are the starting point, and show how the issues coming up are a mixture of ongoing, systemic issues alongside specific questions and concerns relating to GTP or other initiatives and potential impact for a given presentation.

The three case studies then provide between them a cross-section of the analysis and actions coming out from the A4A process. Firstly, an example of one module with innovative approaches looking to ensure that the module design is working for students. Where specific design approaches have proved successful here, such as use of Twitter, these have then fed into subsequent design work and best practice. The second, A14, shows how the process itself supported a module team chair to develop a real insight into their module in spite of initial concerns and expectations about the process and to escalate a specific issue relating to TMA extensions higher up in the faculty.

Lastly, the A15 case study shows how issues of concurrent study can be managed when they come up as a surprise once a module is live.

Whilst individually these case studies may not appear to be that significant, of greater importance is the successful rollout of an approach that:

- Provides meaningful insight on whether a module design is working
- Is supportive in bringing non-technical staff along with the process and
- That illustrates how specific challenges can be managed in presentation

We frequently read about challenges in rolling out new systems or processes in organisations both in higher education and in other industries. For this one to have been established and to have become a business as usual activity successfully illustrates how well the overall package works and provides an exemplar that can be taken forward for other engagement work between

OU units. Subsequent work by the team will look more in depth at outcomes from A4A modules and how the findings have fed back into design work.

Note that in this public version we have anonymised all names and codes of OU modules and qualifications. For OU staff who have access to Intranet, you can download the full results at http://intranet6.open.ac.uk/learning-teaching-innovation/main/data-wrangling

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4. Rienties, B., Cross, S., Marsh, V., Ullmann, T. (2017). Making sense of learner and learning Big Data: reviewing 5 years of Data Wrangling at the Open University UK. *Open Learning: The Journal of Open and Distance Learning*, *32*(3), 279-293. Available at: http://oro.open.ac.uk/49085/
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